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Vibration Feature Extraction Techniques for Fault Diagnosis of Rotating Machinery -A Literature Survey

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The safety, reliability, efficiency and performance of rotating machinery are major concerns in industry. The task of condition monitoring and fault diagnosis of rotating machinery faults is significant but is often cumbersome and labour intensive. Effective and efficient feature extraction techniques are critical for reliably diagnosing rotating machinery faults. Various vibration feature extraction methods have been proposed for different types of rotating machinery during the past few decades. However, limited research has been conducted on synthesizing and analysing these techniques, resulting in apprehension when technicians need to choose a technique suitable for application. This paper presents an updated review of a variety of vibration feature extraction techniques that have demonstrated success when applied to rotating machinery. The literature is categorised into the following groups: time domain, frequency domain, time frequency analysis. The paper will comment on future directions for research on vibration feature extraction for fault diagnosis of rotating machinery.

1. Introduction

Rotating machinery is widely used in today's industry some of which are complex, often with extremely demanding performance criteria. Machine failures can be catastrophic thus resulting in costly downtime. Without effective diagnosis, one is unable to make a reliable prediction of lead-time to failure. Therefore, conducting effective condition monitoring and fault diagnosis is desirable and imperative in industry. However, diagnosing faults in rotating machinery is often a labour-intensive and time-consuming practice. This makes conducting effective and efficient fault diagnosis a challenge for technicians and plant maintainers. Fault diagnosis is conducted typically in the following phases: data acquisition, feature extraction, and fault detection and identification as shown in Figure 1. Effective feature extraction techniques are very critical for the success of fault diagnosis [1].

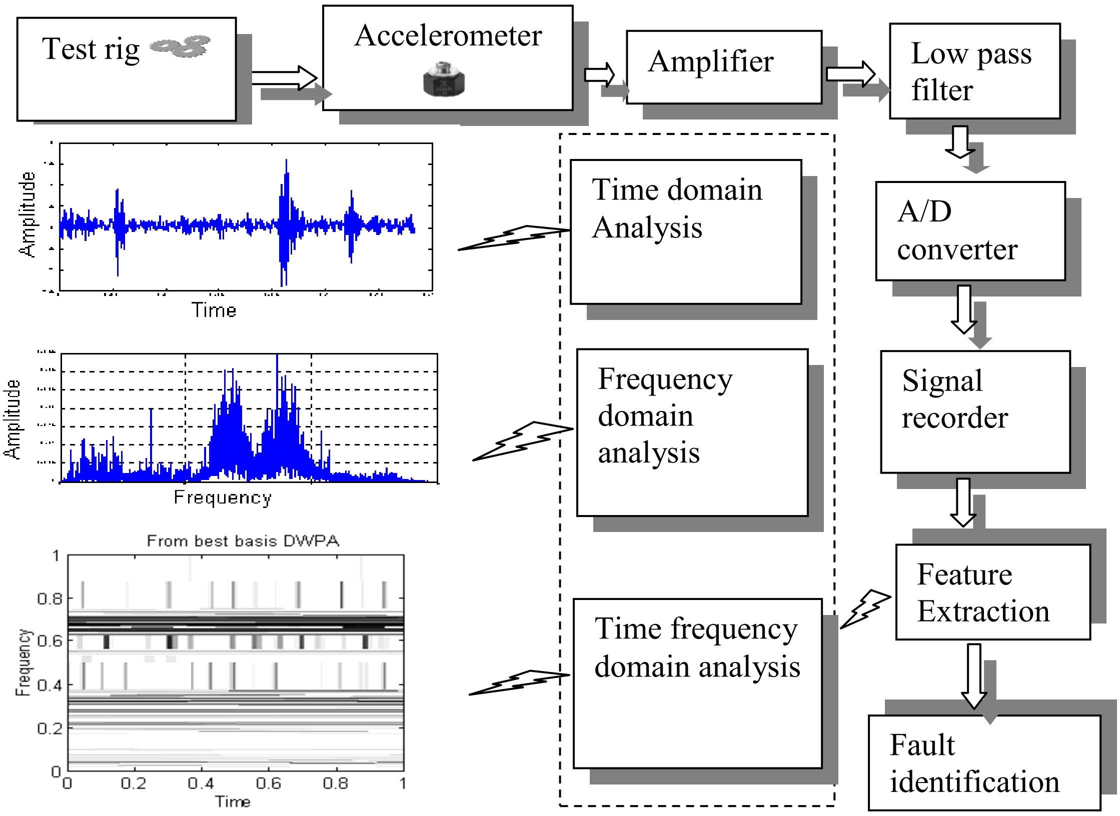

Figure 1. Overview of fault diagnosis based on vibration signals

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Vibration signals collected from sensors and then processed are often contaminated by some noise and can thus be unusable for directly diagnosing machine faults. Features (also called characteristics and signatures) can go undetected without the assistance of certain techniques. Feature extraction techniques can either increase signal to noise ratio or locate certain components in signals to assist detection of machine faults. Numerous vibration techniques have been applied to the fault diagnosis of rotating machinery. Generally vibration techniques range from statistical to model based techniques, and comprise various signal processing algorithms to extract useful diagnostic information from measured vibration signals. In the past twenty years，some research has been conducted into reviewing vibration techniques from different points of view. In the1980's, Mathew and Alfredson presented a review of vibration monitoring techniques in the time and frequency domains for rolling element bearings[2]. McFadden, Smith [3] and Kim [4] included classical non-parametric spectral analysis, principal component analysis, joint time-frequency analysis, the discrete wavelet transform, and a change detection algorithm based on residual generation. Lebold and McClintic [5] reviewed statistical methods for extracting vibration features when diagnosing gearboxes. Tandon and Choudhury reviewed vibration and acoustic measurement techniques for the detection of defects in rolling element bearings [6]. Chow [7] provided a brief review of model-based approaches and signal processing approaches on motor fault detection and diagnosis. In this paper, an updated review of various vibration techniques for a variety of rotating machines is presented and grouped into three categories: time domain, frequency domain, and the joint time frequency domain as shown in Figure 1. In each category, the methods are presented in a unified form given that the current literature which contains a diverse range of techniques, some of which use common principles. Suggestions are also provided for future work.

2. Time Domain

Vibration signals are initially obtained as a series of digital values representing proximity, velocity, or acceleration in the time domain. This section reviews recent research on vibration techniques in the time domain for various types of rotating machinery and categorises these techniques into the following groups (as shown in Figure 2).

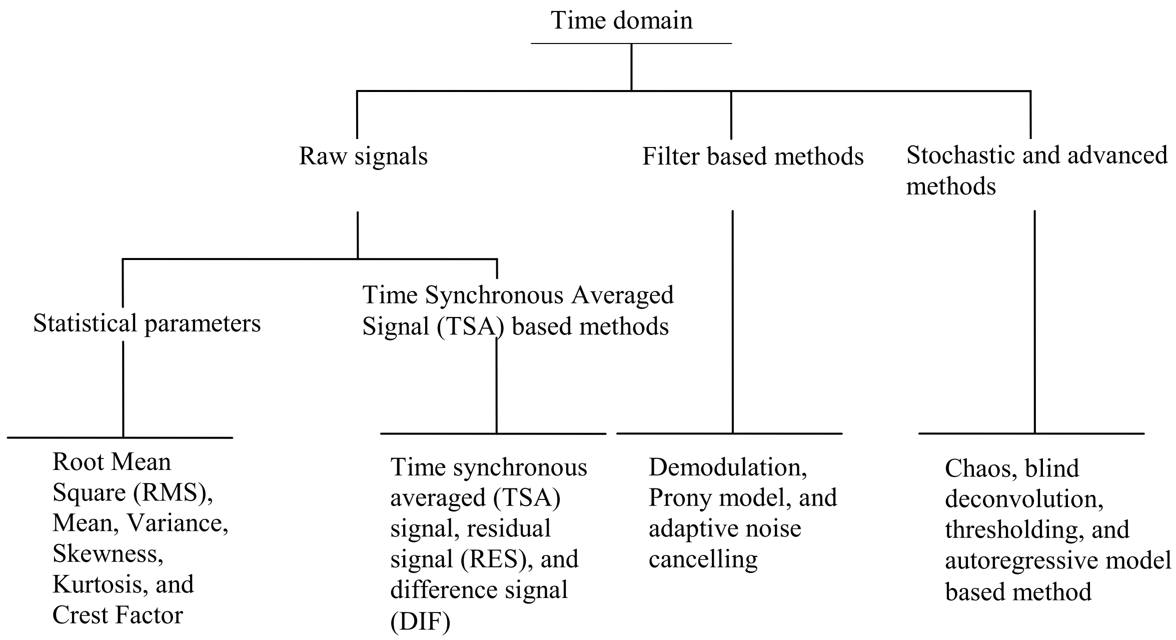

Figure 2. Overview of time domain vibration feature extraction techniques

(1) Statistical parameters, which include Root Mean Square (RMS), Mean, Variance, Skewness, Kurtosis, and Crest Factor

The root mean square (RMS) value and crest factor have been applied in diagnosing bearings and gears [6]. The RMS of a vibration signal is a time analysis feature that measures the power content in the vibration signature. This feature can be very effective when detecting an imbalance in rotating machinery. The most basic approach to measuring defects in the time domain is to use the RMS approach which is often not sensitive enough to detecting incipient faults in particular. Another measure is to use the "crest factor", defined as the ratio of the peak level of the input signal to the RMS level. Therefore, peaks in the time series signal will result in an increase in the crest factor value. This feature is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth breakage on a gear or a defect on the outer race of a bearing.

Statistical analyses of vibration signals have proved to be useful in detecting machinery faults. Tandon [6] showed that the probability density function is correlated with bearing defects. The probability density of acceleration of a bearing in good condition has a Gaussian distribution, whereas a damaged bearing results in non-Gaussian distribution with dominant tails because of a relative increase in the number of high levels of acceleration. Mathew and Alfredson also reported obtaining a near-Gaussian distribution for some damaged bearings. Andrade [8] proposed a comparison of the Cumulative Density Function (CDF) of a target distribution with the CDF of a reference distribution and used the likelihood to successfully detect gear tooth fatigue crack

Statistical moments of these distributions further simplify analysis. Mean, variance, and skewness are the first moment, second moment, and the third moment of probability distribution respectively. Kurtosis is defined as the fourth moment of the distribution and measures the relative peakedness or flatness of a distribution as compared to a normal distribution. Kurtosis provides a measure of the size of the tails of distribution and is used as an indicator of major peaks in a set of data. As rotating machinery faults present themselves, Kurtosis should signal an error due to the increased level of vibration. Kurtosis have been applied to diagnosing bearing, and gearbox faults [9].

The Root mean square, peak value, kurtosis and crest factor have been combined with high frequency resonance techniques and an adaptive line enhancer to detect and localize damage in rolling bearings [10].

(2) Time synchronous averaging based methods which include Time Synchronous Averaged (TSA) Signal, residual signal (RES), and difference signal (DIFS)

The TSA signals are the signals obtained by time synchronous averaging of the initial data and reducing redundant noise. The repetitive signals after TSA can indicate the information related to the faults, which need to be diagnosed. The TSA including FM0 and Comblet [5] requires knowing the repetitive frequency of the desired signal such as defect frequencies of rolling bearings, gears, or shafts. Synchronous averaged signals were utilized to diagnose faults in rolling bearings and gears successfully [11-13].

Residual signals (RES) [5] was used for diagnosing gear faults where RES consisted of the time synchronous averaged signal with the primary meshing and shaft components along with their harmonics removed. RES may be system dependent. Difference signals (DIF) were calculated by removing the regular meshing components from the time synchronous averaged signal. The DIF was used to diagnose gearbox faults effectively [14].

(3) Filter based methods including demodulation, Prony model, and adaptive noise cancelling (ANC)

Filters are widely used in feature extraction techniques for removing noise and isolating signals. Here we generally call all these methods as filter based methods. Filter based methods include demodulation, prony model, and adaptive noise cancelling (ANC).

Demodulation including phase and amplitude demodulation is an important signal processing technique. The amplitude demodulation, also known as envelop, or resonance demodulation, or high frequency resonance demodulation techniques [15] separates low-level, low-frequency signals from background noise, enabling them to be easily measured. In the application of gear faults detection, the amplitude demodulation focused on the fault-induced high-order modulation sidebands around the dominant gear meshing harmonic [16]. It has also been successfully applied to diagnose bearing faults [17]. The phase demodulation emphasised the band associated with the structural resonance excited by the fault-induced impacts [15].

Generally the demodulation procedure starts with using conventional Infinite Impulse Response (IIR) Filters such as Butterworth, Chebyshev, Bessel, and Elliptic in pass band or stop band. Prony's model was an algorithm for finding an IIR filter with a prescribed time domain impulse response. A Prony model based method [18] was applied to bearing faults diagnosis. A recent developed filter, adaptive filter was embedded into an adaptive noise cancelling (ANC) system and showed promise in diagnosing bearing faults [19]. Asynchronous adaptive noise cancelling technology was employed to detect self-aligning roller bearing faults successfully [20].

(4) Stochastic methods (including chaos) and others (blind deconvolution, thresholding, and autoregressive model based method)

Advanced methods such as stochastic parameters have been used to analyse vibrations in the time domain. Chaos, and the correlation dimension in particular, was used to characterise several induced faults of varying severity in a rolling element bearing [21]. The correlation dimension could provide some intrinsic information of an underlying dynamical system, and could be used to classify different faults intelligently [22]. Nirbito [23] proposed and tested the feasibility of blind deconvolution for the enhancement of bearing signals corrupted by noise. The pseudo-phase portrait was sensitive to some rotating machinery faults [24]. Threshold denoising (including hard threshold and soft threshold) were often used to denoise vibration analysis. The threshold denoising methods were usually combined with envelop or some other methods together when diagnosing machinery faults. A soft-thresholding method and hard thresholding method have also been used in diagnosing machine faults [25]. An autoregressive model-based method has also been successfully applied in fault diagnosis [26].

3. Frequency Domain and Time Frequency Domain Feature Extraction Techniques

Features regarding frequency information such as frequency domain features and time frequency domain features are being widely investigated at present. These features can generally indicate machinery faults better than time domain vibration features because characteristic frequency components such as resonance frequency components or defect frequency components can be relatively easily detected and matched to faults.

This section starts from the advent of modern fast Fourier Transform (FFT), then emphasizes various time frequency representations and includes time frequency scale analysis. As shown in Table 1, frequency and time-frequency analysis techniques are being researched to effectively extract coefficients by increasing the order of frequency or time frequency transformation parameters. The techniques were also applied by calculating correlation or logarithmic value of transformation parameters. For example, the power spectrum as a second order spectrum was applied successfully after the spectrum had been used widely in both linear and logarithmic presentations.

Appropriate vibration techniques need to be selected according to applications to obtain optimal diagnostic performance. An overview of developed frequency techniques and time-frequency techniques is given in Table 1, which is followed by some detailed definitions and applications of these techniques.

Table 1. Overview of frequency techniques and time-frequency techniques

First order	Second order	Third order	Fourth order
Spectrum (FFT)	Power spectrum Power cepstrum (logarithm of Power spectrum)	Bicoherence spectrum	
Correlation of spectrum, signal averaging	Cyclostationarity	bilinearity	
Short time Fourier transform (STFT)	Spectrogram Wigner distribution	Wigner bi spectra	Wigner tri spectra
Continuous wavelet transform(CWT)	Scalogram		
Discrete wavelet transform(DWT)			
Discrete wavelet packet analysis (DWPA)			
time-averaged wavelet spectrum (TAWS)			
time-frequency-scale domain (TFS)			

Frequency-domain or spectral analysis of the vibration signals is perhaps the most widely used approach to bearing defect detection. The FFT [27] is the most conventional diagnosis technique and has been widely used to identify the frequency features of signals. These signals can be raw signals or processed signals. For instance, a procedure for obtaining the spectrum of an envelope signal was well established [28] which separated the vibration generated by a defect component from the vibration generated by the other machine elements.

The power spectrum whose amplitude is the square of the amplitude of the spectrum is an effective method to diagnose machinery faults [29]. The higher order spectrum is also called the bispectrum and can be applied to fault diagnosis in motor bearings [30]. The bicoherence spectrum is a third-order spectrum used to measure the phase coherence among three spectral components due to nonlinear wave coupling. The bicoherence has been used to monitor bearing condition [31]. The power cepstrum which is a logarithm of the power spectrum was also applied to machinery fault diagnosis [6].

Cyclostationarity is the second order of a frequency domain synchronised averaging method. The spectral correlation function issued from second-order cyclostationarity is an efficient parameter for the early diagnosis of faults in gear systems. The application of cyclostationarity to early diagnosis of spalling in gear teeth demonstrated the power of this new parameter [32]. A comparison between cyclostationarity and bilinearity was researched and presented in an application to early diagnosis in helicopter gearboxes [33].

During the past decade, time frequency analysis techniques have been studied and applied to machinery fault diagnosis due to their capability of representing signals in both the time and frequency domains. This characteristic of time frequency analysis techniques meet the requirements for analysing vibration signals which are non stationary. Preliminary time frequency analysis techniques ,windowed Fourier transform [34] and Short time Fourier transform (STFT) [35] were applied to monitoring the condition of machinery.

The Wigner distribution [36] and the spectrogram [37] are the most well-known quadratic time frequency representations belonging to the Cohen class which were applied to diagnosing gear faults. The basic nature of such signals causes significant interfering cross-terms, which do not permit a straightforward interpretation of the energy distribution. The directional Choi-Williams distribution (dCWD), was proposed to account for complex-valued time-varying signals, which represented the planar motion of rotating machinery at each instant of time [38]. Directional Wigner distributions (DWDs) defined for the forward and backward pass analytic signals [39] has been applied in analysing the order of rotating machines. The use of the third- and fourth-order Wigner moment spectra, called the Wigner bi- and tri-spectra respectively was used to analyse the signals of rotating machinery [40].

The sliced Wigner fourth-order moment spectra for multiple signals had problems with its application which was due to the existence of non-oscillating cross-terms not smoothed by conventional methods. This technique have been applied to the diagnosis of valve system faults in an engine [41].

The continuous wavelet transform (CWT) has been developed based on the STFT with better time frequency resolution and applied to rotating machinery fault diagnosis [12]. The scalogram – the squared modulus of the CWT [26] was applied in diagnosing gears. Vibration signatures were passed into a harmonic wavelet transform algorithm and the mean square wavelet map [42] to diagnose a rotorcraft planetary geartrain system.

The Discrete wavelet transform (DWT) was used to diagnose spalling in ball bearings [43]. Discrete wavelet packet analysis (DWPA) [44], and discrete wavelet analysis [45] also showed their potential in fault diagnosis. The Matching Pursuit [46] and Basis Pursuit [47] are two recent time frequency adaptive approximation techniques which were applied to diagnosing machinery faults. A time-frequency-scale domain (TFS) technique has also been developed to diagnose machinery faults [48].

4. Conclusion

Vibration feature extraction techniques are improving all the time given advances in disciplines such as statistics, signal processing, and computing science. Time domain techniques include raw signals, filter based signals, stochastic and model based methods. The statistical moments such as mean, covariance, and kurtosis can be calculated and compared with a threshold to detect rotating machinery faults. Statistical parameters are being researched to improve their sensitivity to faults when detecting machinery faults. Filter based methods such as demodulation are being used to effectively separate "fault" vibrations from other irrelevant signals such as noise.

Frequency domain features are generally more consistent in the detection of damage than time domain parameters. Frequency techniques and time frequency techniques are being investigated by increasing the order of transformation parameters. Moreover, time frequency techniques are also being investigated to solve problems such as inter term components between neighbouring frequency bands. In addition, time frequency techniques are also being researched to analyse certain component information required for specific applications. For instance, the dyadic discrete wavelet transform focuses on low frequency bands rather than high frequency bands. Discrete wavelet packet analysis determines packet coefficients both in low frequencies and in high frequencies, making it powerful for fault diagnosis of rotating machineries.

The authors have embarked on a research project to improve the detection and diagnosis of faults in the time frequency domain [47]. The proposed method presents signals with fine resolution and sparsity. Using this new method, time frequency components of vibrations can be clearly shown in a map. This leads to relatively straightforward interpretation of a signal, which is often contaminated by noise.

Furthermore, researchers are increasingly interested in automating the diagnosis procedure using feature extraction techniques. Tools and techniques in artificial intelligent systems such as expert systems, neural networks, and fuzzy inference systems are being used in conjunction with some of the more powerful techniques described above.

The authors have also begun researching the automatic fault diagnosis of rotating machinery. The technique is based on time frequency analysis and neural network techniques. Results of this work will be reported in due course.

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